PREDICTIVE POLICING: A COMPARATIVE STUDY OF THREE HOTSPOT MAPPING TECHNIQUES

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Law enforcement agencies across the U.S. use maps of crime to inform their practice and make efforts to reduce crime. Hotspot maps using historic crime data can show practitioners concentrated areas of criminal offenses and the types of offenses that have occurred; however, not all of these hotspot crime mapping techniques produce the same results. This study compares three hotspot crime mapping techniques and four crime types using the Predictive Accuracy Index (PAI) to measure the predictive accuracy of these mapping techniques in Marion County, Indiana. Results show that the grid hotspot mapping technique and crimes of robbery are most predictive. Understanding the most effective crime mapping technique will allow law enforcement to better predict and therefore prevent crimes.

Vijay O. Lulla Ph.D., Chair

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Introduction

Hotspot mapping has become one of the most widespread methods used to analyze and predict future crime. As of 2007, all law enforcement agencies in the U.S. serving populations of 500,000 or more were analyzing crime using hotspot mapping (Reaves, 2010). Hotspot maps are used to identify the areas where crimes are concentrated, or "hot", relative to the crime distribution in the region. Law enforcement agencies use hotspot maps to prioritize and strategize their efforts in reducing crime. The extensive use of hotspot mapping by law enforcement, and the multiple types of hotspot mapping techniques available to choose from, begs the question - are all hotspot mapping techniques equal in their ability to predict the areas where crimes may occur?

The objective of this study is twofold:

1. Compare three hotspot crime mapping techniques to see if there are differences between the techniques' abilities to predict where offenses may occur.

2. Determine if the accuracy of hotspot crime mapping differs between the types of offenses being mapped.

Background

The origins of mapping crime can be traced back to France, where in 1829 Adriano Balbi and Anfre-Michel Guerry developed maps displaying the relationship between the citizens' education levels and offenses against people and property (Weisburd & McEwen, 1998). Within 20 years crime mapping had spread to England. In 1849 statistician Joseph Fletcher created maps comparing the rate of male incarceration to serious property and violent crimes across counties in England and Wales (Chamard, 2006). Although crime mapping in the U.S. did not emerge until the early 20th century, its sophisticated use among urban sociologists further revealed the strong connection between crime levels and the condition of the social environment.

> [. . . in 1927] Frederic Thrasher superimposed the "location and distribution" of gangs in Chicago on a map of urban areas in the city. He found that gangs were concentrated in areas of the city where social control was weak and social disorganization pervasive. Shaw and Myers reached similar conclusions in [. . . their 1929] study of juvenile delinquency conducted for the Illinois Crime Survey. . . . they show that the home addresses of over 9,000 delinquents are clustered in areas marked by "physical deterioration, poverty and social disorganization". (as cited in Weisburd & McEwen, 1998, p. 8)

The first computer generated crime maps appeared in the in the mid-1960s when a St. Louis police department mapped larcenies from automobiles. This was a great leap forward in the advancement of crime mapping; however, the expense and expertise required to produce these early maps limited the technology's availability to only a handful of law enforcement agencies. The widespread use of computerized crime mapping did not begin until the late 1980s with the advent of the desktop computer.

Computer technology and crime mapping software have evolved significantly over the last 30 years. Complex algorithms and high-speed processors have increased the credibility of the crime fighting strategy known as predictive policing. "*Predictive policing* is the application of analytical techniques – particularly quantitative techniques – to identify lively targets for police intervention and prevent crime or solve past crimes by making statistical predictions" (Perry, McInnis, Price, Smith, & Hollywood, 2013, pp. 1-2). The concept of predictive policing is alluring and can conjure up fanciful ideas if not clearly understood. "Predictions are generated through statistical calculations that produce estimates, at best; like all techniques that extrapolate the future based on the past, they assume that the past is prologue. Consequently, the results are probabilistic, not certain" (Perry et al., 2013, p. 8).

While there are over a dozen predictive policing mapping techniques, this research focused on three methods used to identify crime hotspots: jurisdiction-bounded mapping, grid mapping, and kernel density estimation (KDE). These mapping techniques were selected because they represent fundamental types of hotspot mapping that are commonly discussed in crime mapping literature (S. Chainey, Tompson, & Uhlig, 2008, p. 15). The mapping techniques examined in this study identify crime hotspots. The term "hotspot" is widely used in crime mapping literature, but there is not a definitive definition of what a hotspot is. A hotspot can be a specific location, such as a mall, bar, or parking lot (Sherman, Gartin, & Buerger, 1989, p. 45); or it may adhere to strict guidelines, such as not being more than a standard linear street block, not extending for more than half of a block from either side of an intersection, and being at least a block away from another hotspot (Buerger, Cohn, & Petrosino, 1995, p. 240). While ultimately the definition of a hotspot is unique to each study, there is a common understanding that ". . . a hotspot is an area that has a greater than average number of criminal or disorder events, or an area where people have a higher than average risk of victimization" (Eck & National Institute of Justice (U.S.), 2005, p. 2).

The jurisdiction-bounded crime mapping technique is a type of choropleth map which aggregates the total number of offenses that occur within polygons that are created using a certain jurisdictional boundary system (e.g., census blocks, census tracks, police zones, etc.). Because the area of the polygons differ in size, it is necessary to normalize the raw crime counts within each polygon by dividing them by an appropriate denominator, such as the number of houses for burglaries, or the number of residents for robberies (Spencer Chainey & Ratcliffe, 2005, p. 151). Each polygon is then assigned a color based on its crime percentage rate, with darker colors typically representing hotspots. The census block is the jurisdictional boundary system used in this study. Figure 1 illustrates an example of a census block choropleth hotspot map.

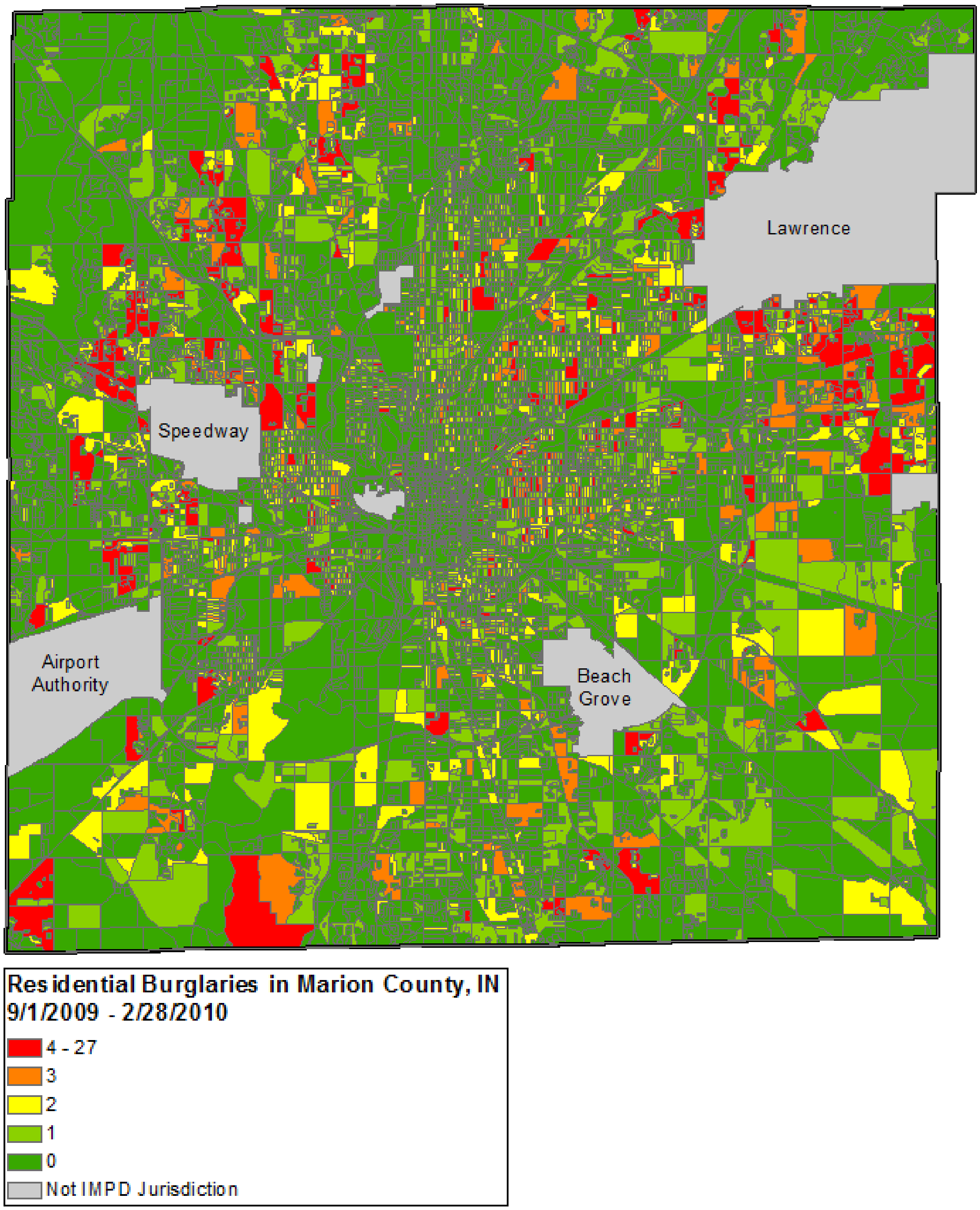

Figure 1. A census block choropleth hotspot map of residential burglaries in Indianapolis, from September 1, 2009 – February 28, 2010.

The grid mapping technique is another type of choropleth map. This technique involves laying a grid of equally proportioned cells over the crime point data and aggregating the crime points within each cell. Different colors are then assigned to each cell based on the total number of offenses within. Unlike the jurisdiction-bounded map, the cells are equal in area; therefore, it is not necessary to normalize the crime data.

The grid mapping technique is able to display the actual crime patterns in greater spatial detail than the jurisdiction-bounded technique if the correct grid cell size is used; the challenge is determining the best grid cell size. If the grid cells are too large the resolution on the map will be coarse, making it difficult to identify the hotspots, while grid cells that are too small produce maps which diminish the clarity of the crime patterns and hotspots.

The literature provides various methods on how to select an appropriate grid cell size. There is no consensus on how this process should be done because different techniques produce more informative results depending on the data being mapped, the application, location, etc.. Chainey and Ratcliffe (2005) suggest dividing the longest extent of the map by 50 and using this distance as the initial grid cell size (p. 153). Hengl (2006) professes a suitable grid resolution is determined by examining the inherent properties of the input data and provides a series of statistical formulas to determine the coarsest, finest, and recommended grid resolution (pp. 1295-1296). Still others examine the physical terrain, such as the average street length, when determining the grid cell size (Kennedy, Caplan, & Piza, 2011, p. 348). Regardless of which suggestion is implemented, experimentation and trial and error of different grid cell sizes is often required when determining the best grid cell size. Figure 2 illustrates an example of a grid choropleth hotspot map.

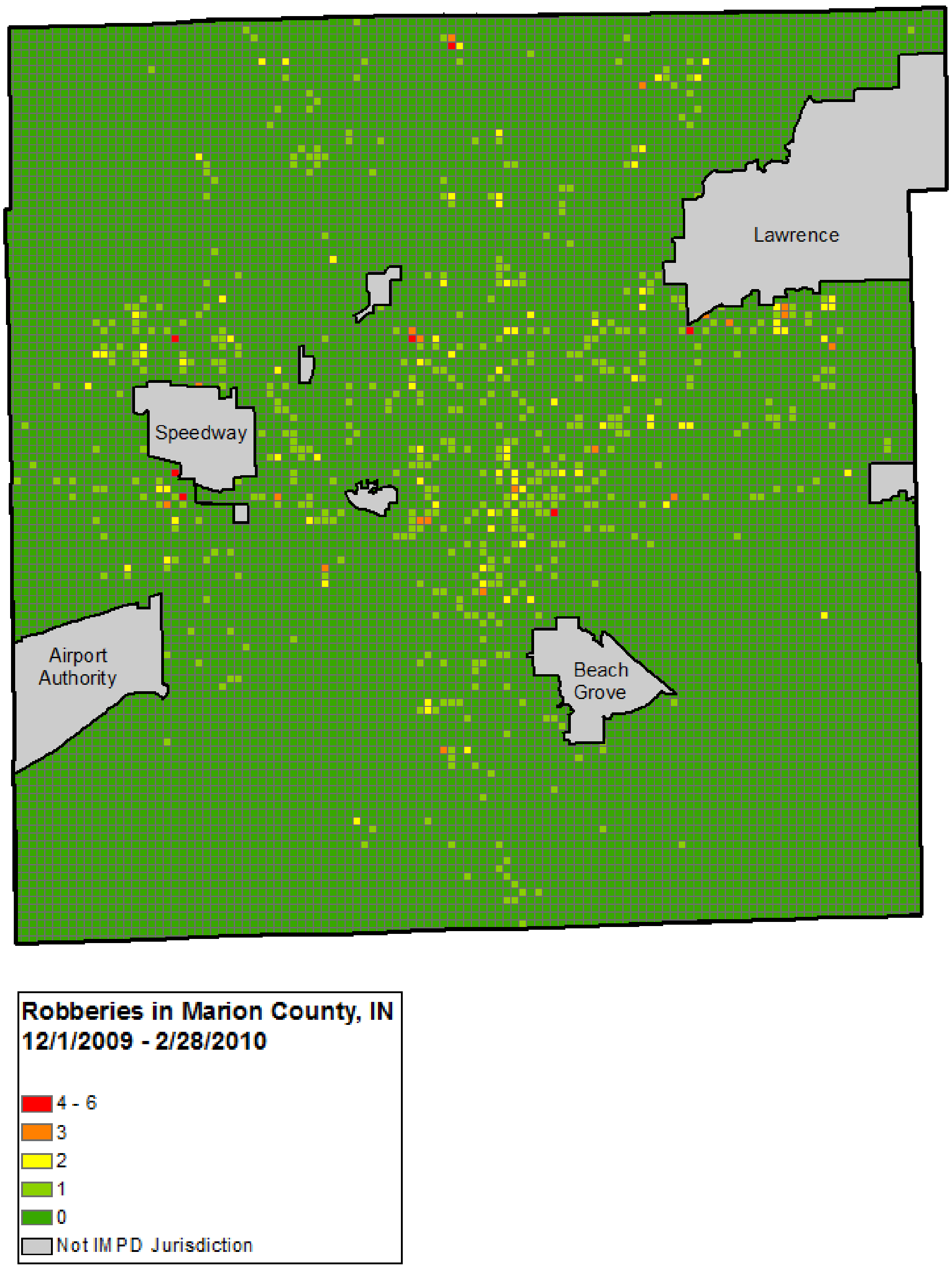

Figure 2. A grid choropleth hotspot map, with 280 meter size cells, displaying robberies in Indianapolis, from December 1, 2009 – February 28, 2010.

Kernel density estimation (KDE) is an interpolation mapping technique which "smoothes" discrete crime points and creates a continuous risk surface that represents the density or volume of crimes distributed across a study area (Eck & Justice, 2005, p. 26; Silverman, 1986) . "The objective is to use crime incident data to identify hot spots based on their proximity to actual crime incidents. A kernel is a standardized weighting function used, in this application, to smooth crime incident data" (Perry et al., 2013, p. 24). The KDE process is explained in the following steps:

1. A fine grid is generated over the point distribution.
2. A moving three-dimensional function of a specified radius visits each cell and calculates weights for each point within the kernel's radius. Points closer to the center will receive a higher weight, and therefore contribute more to the cell's total density value (Figure 3).
3. Final grid cell values are calculated by summing the values of all kernel estimates for each location (Eck & National Institute of Justice (U.S.), 2005, pp. 26-27; Silverman, 1986).

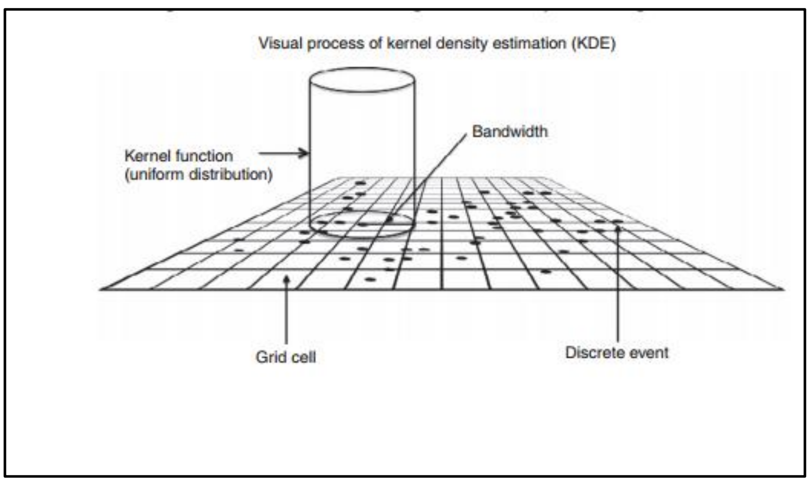

Figure 3. The visual process of kernel density estimation. From "Kernel density estimation and hotspot mapping," by Hart & Zandbergen, 2014, *Policing, 37*(2), p. 309.

KDE is regarded by many as having advantages over other crime mapping techniques due to its growing availability in GIS software, aesthetic appearance, and perceived accuracy with predicting crime hotspots (S. Chainey et al., 2008, p. 8). While the KDE mapping technique is visually appealing and more statistically complex than the other hotspot mapping techniques, it is not without its limitations. The KDE smoothing technique tends to exaggerate the distribution of crime by spreading crime point data into areas where crimes may not have occurred. KDE maps also require several user-defined parameters to be set. In addition to selecting an appropriate grid cell size, the KDE process requires users to select a suitable interpolation method and bandwidth length. An example of a KDE hotspot map is shown in Figure 4.

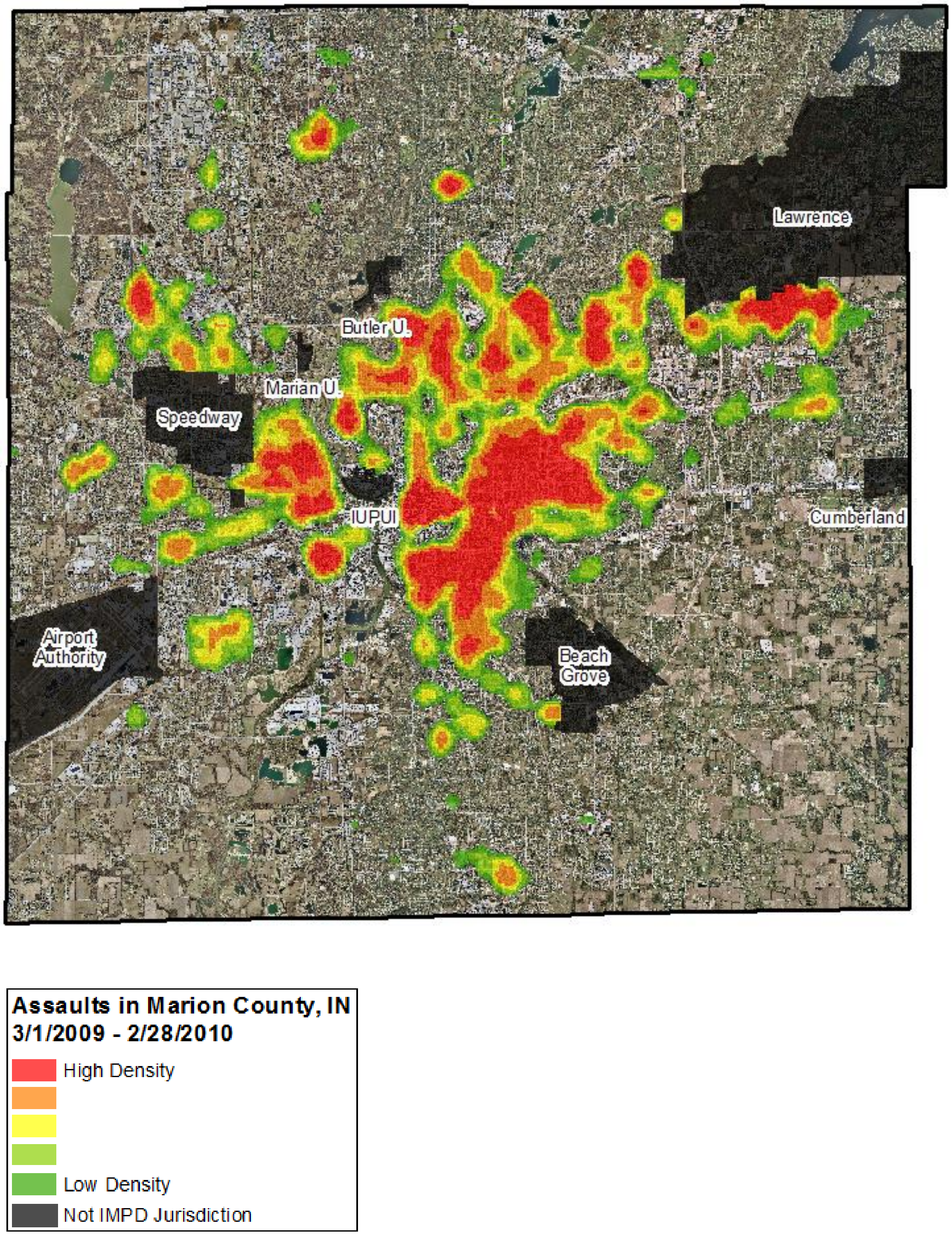

Figure 4. A Kernel Density Estimation (KDE) hotspot map displaying crimes of aggravated assault in Indianapolis, from March 1, 2009 – February 28, 2010.

All three hotspot crime mapping techniques examined in this study produce choropleth maps which by nature suffer from the *modifiable areal unit problem*, or MAUP. The MAUP is ". . . a problem arising from the imposition of artificial units of spatial reporting on continuous geographical phenomenon resulting in the generation of artificial spatial patterns" (Heywood, Cornelius, & Carver, 1998, p. 271). In other words, choropleth maps often distort the cartographic appearance of the actual crime patterns because the crimes are aggregated to polygons with arbitrary boundaries. This may result in producing misleading hotspot maps because it ". . . shades the whole of a region and can often be too coarse to represent the detailed spatial patterns of actual crime events" (Spencer Chainey & Ratcliffe, 2005, p. 151).

Study Area

This study analyzed criminal offenses that occurred within the Indianapolis Metropolitan Police Department's (IMPD) six service districts, which cover an estimated 941 square kilometers. All of IMPD's service districts are located within Marion County, Indiana; home to Indianapolis, the 12th largest city in the U.S., with a 2010 population of 820,445 (Bureau, 2014). As a major U.S. city, the study area includes a diverse mix of land use (residential, commercial, retail, vacant properties, etc.), demographics (ethnic and economic), and industry. A map of the study area is displayed in Figure 5.

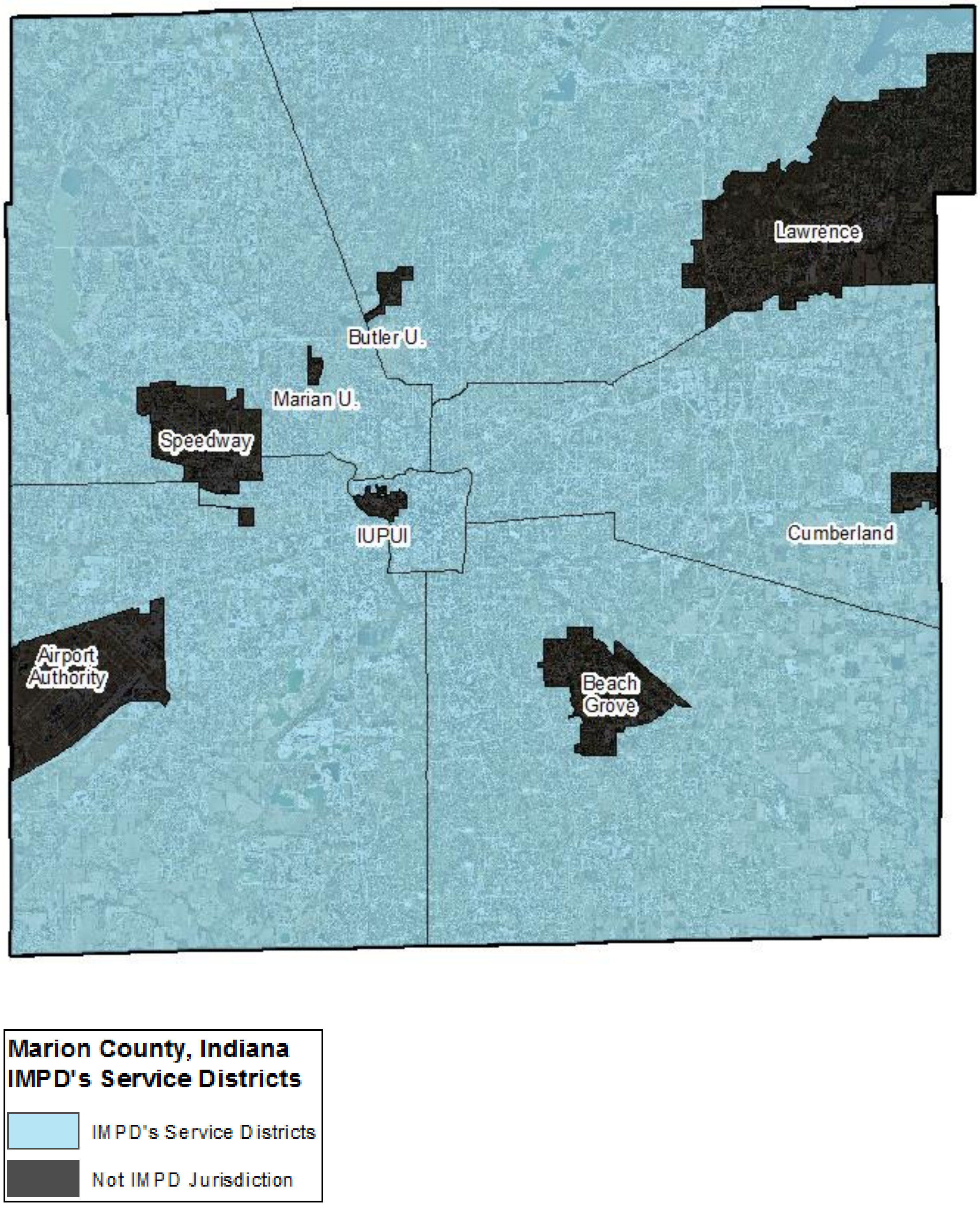

Figure 5. A map of the study area: the Indianapolis Metropolitan Police Department’s service district in Marion County, Indiana.

Data

The data used in this study was from the Indianapolis Metropolitan Police Department's Uniform Crime Reports (UCR). The Uniform Crime Reporting Program is administered by the FBI. It began in 1929 as a way to collect crime statistics from police departments across the United States. The program standardizes how crime data is submitted in order to produce uniformity in nationwide crime reporting (FBI, 2004). As part of the standardization process, offenses were strictly defined and divided into two groups – Part I and Part II. Part I offenses are more serious; they include eight crime groups that are further categorized into 22 crime types. These crime groups include: criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft, and arson. The Part II group is made up of 21 less serious offenses.

The UCR data used in this study are criminal offenses that occurred with the IMPD's area of jurisdiction. Some of the offenses have been cleared by the IMPD by arrest or exceptional means, while other offenses remain unsolved. The UCR data does not indicate whether or not the offender was convicted of an offense. The IMPD publishes their UCR data annually and makes it available to the public. The data was obtained from the IMPD's website (http://www.indy.gov/egov/city/dps/impd/crimes/pages/ucrdownload.aspx). The data has been geocoded using the reported addresses based on the street centerline rather than on parcels, so the points represent an estimation of where the offenses occurred, not necessarily an exact location. Also included in the UCR data are the date and time of when the offense took place. If a time span was reported for a given offense, the earliest date or time the offense could have taken place is recorded.

Four Part I UCR crime groups were selected for analysis: aggravated assault, residential burglary, robbery, and vehicle theft. The study's timeframe spans two years: March 1, 2009 – February 28, 2011. These crime groups were selected because they are similar to the types of offenses analyzed in a comparable 2008 study, *The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime*. The authors of this study examined residential burglary, street crime, theft from a vehicle, and theft of a vehicle, because ". . . they are groupings that are regularly analyzed by police and crime reduction practitioners; therefore, the implications of the research would be accessible and could be more readily translated into policing and crime reduction practice" (S. Chainey et al., 2008, p. 11).

Before the data could be analyzed, it had to first be cleaned and organized. "Cleaning" the data consisted of removing unwanted offense records from the dataset. First, records tagged with an X11 beat code were removed from the data. X11 denotes an offense with an unknown location of occurrence. Next, simple assault offenses were removed because they are not a Part I offense – they are a Part II offense that are included in the Part I UCR ". . . as a quality control matter and for the purpose of looking at total assault violence" (FBI, 2004, p. 26). Non-residential burglaries were also removed because the data needed to normalize this type of offense was not available. Finally, offense data that occurred outside of the study's timeframe was removed.

The study's two-year timeframe spans across three calendar years; therefore, offense data was used from the IMPD's 2009, 2010, and 2011 UCRs. Each of the three UCRs contain offenses that occurred in a different calendar year than the UCR in which they were reported. For example, the 2009 UCR includes a small number of offenses that occurred in 2007 and 2008. Lieutenant Don Weilhamer, Jr., of the IMPD explained the reason this happens is because occasionally the reporting process can be delayed and miss the UCR's monthly submission deadline. Because the IMPD is obligated to report the offense data, the offenses are included in the next UCR submission, which is sometimes the following calendar year (D. Weilhamer Jr., personal communication, September 30, 2014).

The IMPD organizes their UCR data into dozens of crime categories. The four crime groups used in this study (aggravated assault, residential burglary, robbery, and vehicle theft) make up 28 of these crime categories. The 28 crime categories were consolidated and organized into the four crime groups as depicted in Table 1.

Table 1

Crime Types within each Crime Group & Number of Offenses (3/1/2009 - 2/28/2011)

Crime Group: Aggravated Assault	**Offenses**
ASSAULT – GUN	2,003
ASSAULT – HAND, FIST	2,777
ASSAULT – KNIFE	1,681
ASSAULT – OTHER WEAPON	4,584
Aggravated Assault Total	*11,045*
Crime Group: Residential Burglary	
BURGLARY – ATTEMPT – RESIDENTIAL DAY	1,453
BURGLARY – ATTEMPT – RESIDENTIAL NIGHT	1,004
BURGLARY – FORCED ENTRY – RESIDENTIAL DAY	11,233
BURGLARY – FORCED ENTRY – RESIDENTIAL NIGHT	6,253
BURGLARY – NO FORCE – RESIDENTIAL DAY	3,046

BURGLARY – NO FORCE – RESIDENTIAL NIGHT	2,171
Residential Burglary Total	*25,160*
Crime Group: Robbery	
ROBBERY – ARMED BANK	33
ROBBERY – ARMED CHAIN STORE	88
ROBBERY – ARMED COMMERICIAL HOUSE	665
ROBBERY – ARMED HIGHWAY	2,041
ROBBERY – ARMED MISCELLANEOUS	30
ROBBERY – ARMED OIL STATION	105
ROBBERY – ARMED RESIDENCE	691
ROBBERY – ATTEMPT – STRONG-ARMED	350
ROBBERY – ATTEMPT – ARMED	621
ROBBERY – STRONG-ARMED BANK	29
ROBBERY – STRONG-ARMED CHAIN STORE	23
ROBBERY – STRONG-ARMED COMMERICIAL HOUSE	345
ROBBERY – STRONG-ARMED HIGHWAY	1,438
ROBBERY – STRONG-ARMED MISCELLANEOUS	41
ROBBERY – STRONG-ARMED OIL STATION	24
ROBBERY – STRONG-ARMED RESIDENCE	624
Robbery Total	*7,148*
Crime Group: Vehicle Theft	
VEHICLE THEFT	8,389
VEHICLE THEFT – ATTEMPT	620
Vehicle Theft Total	*9,009*
Total Offenses	**52,362**

Methodology

To compare the accuracy of predictive hotspot crime maps, the data was organized chronologically and divided into "input data" and "measurement data." The day that separates the input data from the measurement data is referred to as the "measurement date." The approach to selecting a measurement date for this study followed the methods used in Chainey et al.'s (2008, p. 11). Specifically, the measurement date could not be a major holiday and should be representative of a day in Indianapolis in which people go about their "normal" day-to-day routine. The measurement date of Monday, March 1 2010 met this criteria and was selected for this study. The input data consists of all offenses that occurred before the measurement date. The measurement data consists of offenses that took place on and after the measurement date. Although all of the data used in this study is historic, for this investigation the input data was used as retrospective data while the measurement data was used as "future" data.

The offense data was further divided into four timeframes, each three months long (Table 2).

Table 2
Input Data Timeframes

3 Months	6 Months	9 Months	12 Months
12/1/2009 - 2/28/2010	9/1/2009 - 2/28/2010	6/1/2009 - 2/28/2010	3/1/2009 - 2/28/2010

The data in each time period is an aggregation of all offense data up to the measurement date. In other words, the 3 months of input data include the 3 months of all offenses that occurred before the measurement date; the 6 months of input data include the 6 months of all offenses that occurred before the measurement date, and so on. The year of measurement data was also separated into four, three month long timeframes as displayed in Table 3. The offense data represented in each of these time periods is an aggregation of all the offenses that occurred in the timeframe on and after the measurement date.

Table 3

Measurement Data Timeframes

3 Months	6 Months	9 Months	12 Months
3/1/2010 - 5/31/2010	3/1/2010 - 8/31/2010	3/1/2010 - 11/30/2010	3/1/2010 - 2/28/2011

There are a variety of ways to measure the predictive accuracy of hotspot mapping techniques. Hit rate is the percentage of offenses that occur in areas where offenses are predicted to occur (i.e. hotspots) with respect to the total number of offenses in the dataset. The hit rate method, while useful and straightforward, fails to factor in the size of the areas where offenses are predicted to occur – a significant shortcoming when you consider the following: "…a hit rate could be 100 per cent, but the area where crimes are predicted to occur could cover the entire study area – a result of little use to practitioners who have the need to identify where to target resources" (S. Chainey et al., 2008, p. 12).

Given this limitation, the measurement formula used in this study is the prediction accuracy index (PAI) as first introduced by Chainey et al., 2008. According to Chainey et al.,

> This index has been devised to consider the hit rate against the areas where crimes are predicted to occur with respect to the size of the study

> area. The PAI is calculated by dividing the hit rate percentage (the percentage of crime events for a measurement data time period falling into the areas where crimes are predicted to occur determined from input data, i.e. the crime hotspots) by the area percentage (the percentage area of the predicted areas (the hotspots) in relation to the whole study area). (2008, pp. 12, 14)
>
> The formula for the PAI is as follows:
>
> $$\frac{\left(\frac{n}{N}\right)\times 100}{\left(\frac{a}{A}\right)\times 100} = \frac{HitRate}{AreaPercentage} = PAI \qquad (1)$$
>
> *n* is the number of offenses in areas where offenses are predicted to occur (i.e. hotspots), *N* is the total number of offenses that occur in the study area, *a* is the total areas where offenses are predicted to occur (i.e. hotspots), and *A* is the total study area. (S. Chainey et al., 2008, p. 14)

Finding an equal percentage of hit rate and area percentage will produce a PAI value of 1. PAI values greater than 1 have hit rate percentages that are greater than their area percentages, while PAI values less than 1 have hit rate percentages that are less than their area percentages. For example, if 4% of measurement data occurs within hotspots that make up 2% of the study area, a PAI value of 2 is produced. In short, larger PAI values denote a greater number of future offenses occurring in hotspots that are smaller than the study area.

In order to determine if the accuracy between hotspot maps differs between hotspot mapping techniques, or between crime types, PAI measurements must first be calculated. First, 48 hotspot maps were created using input data from each of the four input data timeframes, four crime types, and three mapping techniques (4 timeframes x 4 crime types x 3 mapping techniques = 48 hotspot maps). This is displayed in Appendix A.

Next, measurement data from each timeframe was laid over each of the 48 hotspot maps. The measurement data laid over the hotspot maps allowed for the calculation of the hit rate and area percentage, producing 192 PAI measurements. A visual of this process is displayed in Appendix B.

To determine if there are differences in the ability of hotspot mapping techniques to predict where crimes may occur, all of the PAI values calculated for each hotspot mapping technique were aggregated and averaged together to produce three mean PAI values, one for each hotspot mapping technique. This equated to averaging:

- 64 PAI values for the census block hotspot mapping technique
- 64 PAI values for the grid hotspot mapping technique
- 64 PAI values for the KDE hotspot mapping technique

A visual of this process is shown in Appendix C.

To find out if the ability to predict where crimes may occur differed by crime type, all of the PAI values for each crime type were aggregated and averaged together across the hotspot mapping techniques. This produced four mean PAI values, one for each crime type. This equated to averaging:

- 48 PAI values for aggravated assault
- 48 PAI values for residential burglary
- 48 PAI values for robbery

- 48 PAI values for vehicle theft

Appendix D displays a visual of this process.

All hotspot mapping techniques require the user to set certain parameters before a hotspot map can be produced. Given the significant influence the parameter selection has on the resulting hotspot maps, the parameters used in this study are based on suggestions found in literature.

ArcMap was used to create the census block choropleth hotspot maps. The 2010 U.S. census blocks, which include population and housing unit counts, were used in the study. The point data was joined to the census blocks using the “Spatial Join” tool in ArcMap. The default settings of the Spatial Join tool were used when creating these maps, specifically, the “intersect match option” and the “join one-to-one join operation.” These settings match the crime points to the census blocks with which they intersect. Crime points located within more than one census block are not duplicated; they are assigned to only one census block.

Because the census blocks vary in size the raw crime counts for each census block were normalized. The normalization process consisted of dividing the number of crimes that occurred in each census block by an appropriate denominator, which was determined by the crime type. Residential burglaries were divided by the number of residential housing units in each block, and crimes of aggravated assault, robbery, and vehicle theft were divided by the number of residents in each census block (Spencer Chainey & Ratcliffe, 2005, pp. 374-375).

ArcMap was also used to create the grid hotspot maps using the “fishnet” tool. A fishnet is simply a grid made up of equal sized cells. The appropriate cell size was determined for each input dataset based on the geometry of the point patterns, specifically, the distance between the crime points using the following formula introduced by Hengl (2006).

$$p = 0.25 \times \sqrt{\frac{A}{N}} \qquad (2)$$

p is the grid (pixel) cell size, A is the study area in square meters, and N is the total number of observations (i.e. crime points) (pp. 1289-1290). The 0.25 (mm) part of the formula is one-half the distance suggested by McBrantney, Mendoca, and Minasny who state:

> . . . there should be at least 2 x 2 pixels to represent smallest rounded objects of interest and at least two pixels to represent the width of elongated objects. The smallest objects are typically of size 1 x 1 mm on the map, so that the grid resolution can be determined using the p = 0.5 mm rule. (as cited in Hengl, 2006, p. 1286)

However, the 0.5 mm rule is valid only with regular point samples, not random or clustered distribution of points like the crime data used in this study. With random point data “…the average spacing between closest point pairs is approximately half the spacing between closest point pairs in regular point samples. . . . because random sampling has equal probability of producing totally clustered and totally regular samples” (Hengl, 2006, pp. 1289-1290).

Table 4 displays the grid cell sizes used to create the grid hotspot maps based on the number of crime points in each dataset.

Table 4
Grid cell sizes for grid hotspot maps

Assault	Burglary	Robbery	Vehicle Theft
3 Mo Asslt Grid Map # of Crime Points: 1088 **Grid Cell Size: 233m^2**	3 Mo Burg Grid Map # of Crime Points: 2554 **Grid Cell Size: 152m^2**	3 Mo Robb Grid Map # of Crime Points: 748 **Grid Cell Size: 280m^2**	3 Mo VT Grid Map # of Crime Points: 1115 **Grid Cell Size: 230m^2**
6 Mo Asslt Grid Map # of Crime Points: 2437 **Grid Cell Size: 155m^2**	6 Mo Burg Grid Map # of Crime Points: 6333 **Grid Cell Size: 96m^2**	6 Mo Robb Grid Map # of Crime Points: 1763 **Grid Cell Size: 183m^2**	6 Mo VT Grid Map # of Crime Points: 2266 **Grid Cell Size: 161m^2**
9 Mo Asslt Grid Map # of Crime Points: 3940 **Grid Cell Size: 122m^2**	9 Mo Burg Grid Map # of Crime Points: 9943 **Grid Cell Size: 77m^2**	9 Mo Robb Grid Map # of Crime Points: 2884 **Grid Cell Size: 143m^2**	9 Mo VT Grid Map # of Crime Points: 3425 **Grid Cell Size: 131m^2**
12 Mo Asslt Grid Map # of Crime Points: 5346 **Grid Cell Size: 105m^2**	12 Mo Burg Grid Map # of Crime Points: 12982 **Grid Cell Size: 67m^2**	12 Mo Robb Grid Map # of Crime Points: 3799 **Grid Cell Size: 124 m^2**	12 Mo VT Grid Map # of Crime Points: 4476 **Grid Cell Size: 115m^2**

The kernel density hotspot maps were created using CrimeStat III, a free spatial statistic program for analyzing crime point locations. Unlike ArcMap, CrimeStat III allows the user to manipulate all of the KDE parameters (method of interpolation, grid cell size, and bandwidth length). The ability to adjust these parameters was important in order to implement the recommendations found in literature.

Two of the three parameter settings used in this study, method of interpolation and bandwidth length, are based on findings from Hart, and Zandbergen's (2014) research on the effects the interpolation method, grid cell size, and bandwidth settings have on KDE hotspot maps used to forecast crime. In their study, Hart et al. adjusted these three parameters and examined the effects the different settings had on the predictive accuracy of the KDE hotspot maps. For the interpolation method Hart et al. (2014) suggest using either the triangular or quartic interpolation method, depending on the crime type, as they were methods which produced consistently high predictive accuracy scores. This study used the triangular interpolation method for crimes of aggravated assault, and the quartic method for robbery, residential burglary, and vehicle theft (pp. 316-317).

In terms of selecting a bandwidth, Hart et al. (2014) recommend using a smaller bandwidth because their ability to successfully forecast crime declined as they increased the bandwidth search radius. The authors suggest "…a standard search radius, equal to the smaller of the length or width of a study area, divided by between 30 and 50 be used for determining an appropriate KDE bandwidth" (p. 316). A bandwidth of 0.9 kilometer was used for all the KDE hotspot maps in this study. This length was determined by dividing the shorter length of the study area (32 km) by 30 (1.07 km) and by 50 (0.64 km) and using the mean of these two calculations.

Hart et al.'s suggestion of selecting a grid cell size was not followed for this study. Instead, the methods recommended by Hengl (2006) were implemented, and the same grids created for the grid hotspot maps were used for the KDE hotspot maps. The decision to use Hengl's method over the one put forward by Hart et al. is because Hengl's research on the topic of selecting an appropriate grid size is more thorough.

The census block choropleth, grid choropleth, and kernel density hotspot mapping techniques all produce a count of the number of crime points that fall within a defined area. In order to determine which areas on the map are "hot," choropleth thresholds need to be set by selecting a classification method and the number of classes. The quantile classification method and five classes are the choropleth thresholds used for all three of the hotspot mapping techniques. The quantile classification method was selected for this study because it is the choice method for comparing the different crimes types, each with differing values (number of offenses), against each other (Santos, 2005, p. 213). It is also the classification method often used when comparing data mapped at different time periods, as is the data used in this study (MacEachren, 1995, p. 47). Five classes were selected because it falls between the upper and lower limits of the suggested number of classes to use in a choropleth map (Harries & National Institute of Justice (U.S.), 1999, p. 50).

Results

This study examined three hotspot crime mapping techniques commonly used to generate hotspot maps (Weir & Bangs, 2007) to determine if differences exist between the mapping techniques' ability to predict the areas where offenses may occur. The study also looked at four different crime types (aggravated assault, residential burglary, robbery, and vehicle theft) to see if the type of crime being mapped had any influence on the hotspot maps' ability to predict the areas where the respective offenses may occur in the future.

Table 5 displays the mean PAI values from the three hotspot mapping techniques.

Table 5
Mean PAI Values for Hotspot Mapping Techniques

Hotspot Mapping Technique	**Mean PAI Value**
Jurisdiction Boundary (Census Block)	*3.52*
Grid	**28.88**
Kernel Density Estimation (KDE)	4.19

The value in bold indicates the highest PAI value and the italicized value indicates the lowest PAI value.

The grid hotspot mapping technique proved to be the best hotspot mapping technique for predicting the areas where offenses may occur. The results show the grid hotspot mapping technique producing an average PAI value well above the other mapping techniques, followed by kernel density estimation, and the census block technique having the lowest average PAI value.

The research also discovered that the type of offense being mapped affects the hotspot maps' ability to predict the areas where the respective offenses may occur in the future. Table 6 displays the mean PAI values, across the hotspot mapping techniques for the four crime types examined in this study.

Table 6
Mean PAI Values for Crime Types

Crime Type	**Mean PAI Values**
Assault	13.76
Burglary	10
Robbery	**18.2**
Vehicle Theft	*6.82*

The value in bold denotes the highest PAI value and the italicized PAI value indicates the lowest PAI value.

In this study the hotspot maps had a greater ability at predicting the areas where future robberies were going to occur than the three other crime types.

To further examine how hotspot mapping techniques and crime types influence PAI values, the mean PAI values were calculated for each hotspot mapping technique, by crime type. Table 7 displays the consistency of these mean PAI values; with the grid hotspot mapping technique and robbery producing the highest mean PAI values.

Table 7
Average PAI Values for Hotspot Mapping Technique, by Crime Type

Hotspot Mapping Technique	**Assault**	**Burglary**	**Robbery**	**Vehicle Theft**
Jurisdiction Boundary (Census Block)	3.94	2.64	*5.05*	2.45
Grid	**33.12**	**23.75**	***44.38***	**14.25**
Kernel Density Estimation (KDE)	4.21	3.6	*5.19*	3.75

The values in bold indicate the highest PAI values by mapping technique, and the italicized values indicates the highest PAI values by crime type.

Discussion/Conclusion

The results of this research show that not all hotspot mapping techniques are equal in their ability to forecast the areas where crimes may occur. Not only did the grid hotspot mapping technique consistently produce greater PAI values than the other mapping techniques, but also its mean PAI value (28.88) is more than seven times greater than the kernel density estimation technique's mean PAI value (4.19). To understand why the grid hotspot mapping technique produced PAI values that were much larger, one must examine the area percentages within the PAI values.

As discussed earlier, PAI is the formula used in this study to measure the predictive accuracy of the hotspot mapping techniques. All of the PAI values produced in this study are a reflection of hit rate percentages divided by area percentages. When examining these factors it becomes clear that the reason the grid hotspot mapping technique produced PAI values that are so much greater is because of how small the mean area percentage is for the grid hotspot maps compared to the other hotspot mapping techniques (Table 8).

Table 8
Mean PAI Area % for each Hotspot Mapping Technique

Hotspot Mapping Technique	**Mean Area %**
Census Block	2.56%
Grid	0.11%
KDE	16.31%

The reason the mean area percentages differ between the hotspot mapping techniques is because each technique identifies hotspots differently. When the census block hotspot map identifies a "hot" census block, the area is likely much larger than when the grid hotspot map identifies a “hot” cell due to the great difference in the average size of these areas. The mean area of the census blocks in this study is 62,364 square meters, compared to 116.5 square meters for the grid hotspot mapping technique. KDE identifies the “hot” areas on a map by looking at the high density of crime in relation to the rest of the study area. Although the same grids used in the grid hotspot maps were also used to make the KDE maps, the KDE hotspots are much larger than the hotspots produced by the other mapping techniques due to KDE’s “smoothing” process which tends to exaggerate the “hot” areas.

Another factor that has influenced the results of this study is the size of the study area. This becomes clear when comparing this study’s results to Chainey et al.’s, which resulted in KDE having the highest mean PAI value. The crime types, number of crimes analyzed, hotspot mapping techniques used, and the timeframes of the two studies are similar. What is significantly different is the size of the study area in each study. This study’s study area (941 square kilometers) is about 25 times larger than Chainey et al.’s study area (37 square kilometers). Given that the study area is the denominator of the area percentage in the PAI formula, it has a significant influence on the PAI value and is likely a contributing factor as to why the two studies show differing results in which hotspot crime mapping techniques yielded the highest mean PAI value.

The findings also revealed that the accuracy of hotspot mapping used to predict the areas where offenses may occur in the future differs between the types of offenses being mapped. One of the limitations of this study is that it did not examine the influences socio-economic levels or environmental characteristics may have had on the hotspots that were mapped, so it is not possible to know for certain how these factors affected the mean PAI values for each type of crime mapped; however, it is possible to speculate factors which may have contributed to the differences. In Chainey et al.'s study, street crime (robbery of personal property and theft from a person) yielded the highest mean PAI value and vehicle theft the lowest. According to Chainey et al.:

> . . . street crime predominantly occurred in areas where shops, bars, restaurants, markets and other forms of retail and entertainment concentrate – places that are prone to the opportunities to commit street crime. This type of land use tends to be clustered at particular localities, meaning that the opportunity for street crime is similarly highly concentrated. These types of land use also tend to be static, in that they do not shift around the urban landscape but instead become a stationary part of the area's environmental fabric. (2008, p. 24)

These components, coupled with the understanding that crime patterns tend to highlight the areas which allow for opportunities to commit crime, are likely the main reasons the hotspot maps of street crime resulted in the highest mean PAI value in Chainey et al.'s study. One could speculate this same rational can explain why the robberies in this study produced the highest PAI values given the similar nature of the crime types. Vehicle thefts, as opposed to robberies, are transient and more dispersed across the study area; therefore, these types of crime patterns are continually shifting making the retrospective data less reliable in terms of predicting where future offenses may occur.

Other limitations to this study involve the availability of certain data and the method by which the data was organized. This study was unable to examine non-residential burglaries because the non-residential unit data, necessary to normalize the census block burglary hotspot maps, was not readily available. Secondly, the organization of the tables in this study does not follow the "tidy data" rules as described by Hadley Wickham, where each variable is a column, each observation is a row, and each type of observational unit forms a table (2014, p. 4). The benefit of having the data organized in this way is that ". . . it makes it easy for an analyst or computer to extract needed variables because it provides a standard way of structuring a dataset" (Wickham, 2014, p. 5). Not having the data organized the "tidy" way slows the time it takes to analyze the data and increases to potential for errors.

This study has shown the most predictive hotspot crime mapping technique and predictive type of crime using hotspot mapping in Marion County, Indiana. Hotspot crime mapping is just one technique used by law enforcement to strategize their crime-fighting efforts. Advances in technology have built on the concepts used in hotspot crime mapping and contributed to the growth of the predictive policing industry. An example of this is PredPol, a leading predictive policing company with proven results. Similar to hotspot mapping it relies on historic data (type of crime, place of crime, and time of crime); however, rather than simply mapping the data, the data is also analyzed using a unique algorithm based on criminal behavior patterns to highlight the areas the police officers should patrol at any given time of the day.

PredPol reduces the amount of time crime analysts are spending looking over the data and creating maps, allowing more time for law enforcement to put the predictive policing techniques into practice. Multiple cities using PredPol have shown a reduction in crime, including the Los Angeles Police Department's Foothill Division which ". . . saw a 20% drop in predicted crimes year over year from January 2013 to January 2014" (PredPol, 2014). Improved predictive mapping tools, such as PredPol, are needed by practitioners to produce quicker and more standardized ways of analyzing crime data to effectively reduce crime.

Appendix A

48 Hotspot Crime Maps

Mapping Technique: Census Block (CB)				
	Assault	**Burglary**	**Robbery**	**Vehicle Theft**
3 Mo (12/1/2009 - 2/28/2010)	3 Mo Assault CB Map	3 Mo Burglary CB Map	3 Mo Robbery CB Map	3 Mo VT CB Map
6 Mo (9/1/2009 - 2/28/2010)	6 Mo Assault CB Map	6 Mo Burglary CB Map	6 Mo Robbery CB Map	6 Mo VT CB Map
9 Mo (6/1/2009 - 2/28/2010)	9 Mo Assault CB Map	9 Mo Burglary CB Map	9 Mo Robbery CB Map	9 Mo VT CB Map
12 Mo (3/1/2009 - 2/28/2010)	12 Mo Assault CB Map	12 Mo Burglary CB Map	12 Mo Robbery CB Map	12 Mo VT CB Map
Hotspot Mapping Technique: Grid				
	Assault	**Burglary**	**Robbery**	**Vehicle Theft**
3 Mo (12/1/2009 - 2/28/2010)	3 Mo Assault Grid Map	3 Mo Burglary Grid Map	3 Mo Robbery Grid Map	3 Mo VT Grid Map
6 Mo (9/1/2009 - 2/28/2010)	6 Mo Assault Grid Map	6 Mo Burglary Grid Map	6 Mo Robbery Grid Map	6 Mo VT Grid Map
9 Mo (6/1/2009 - 2/28/2010)	9 Mo Assault Grid Map	9 Mo Burglary Grid Map	9 Mo Robbery Grid Map	9 Mo VT Grid Map
12 Mo (3/1/2009 - 2/28/2010)	12 Mo Assault Grid Map	12 Mo Burglary Grid Map	12 Mo Robbery Grid Map	12 Mo VT Grid Map
Hotspot Mapping Technique: Kernel Density Estimation (KDE)				
	Assault	**Burglary**	**Robbery**	**Vehicle Theft**
3 Mo (12/1/2009 - 2/28/2010)	3 Mo Assault KD Map	3 Mo Burglary KD Map	3 Mo Robbery KD Map	3 Mo VT KD Map
6 Mo (9/1/2009 - 2/28/2010)	6 Mo Assault KD Map	6 Mo Burglary KD Map	6 Mo Robbery KD Map	6 Mo VT KD Map
9 Mo (6/1/2009 - 2/28/2010)	9 Mo Assault KD Map	9 Mo Burglary KD Map	9 Mo Robbery KD Map	9 Mo VT KD Map
12 Mo (3/1/2009 - 2/28/2010)	12 Mo Assault KD Map	12 Mo Burglary KD Map	12 Mo Robbery KD Map	12 Mo VT KD Map

Appendix B

192 PAI Calculations: Measurement Data over Hotspot Crime Maps

Hotspot Mapping Technique: Census Block (CB)				
	Assault	**Burglary**	**Robbery**	**Vehicle Theft**
Input Crime Data (ICD)				
3 Mo (12/1/2009 - 2/28/2010)	3 Mo Asslt CB Map	3 Mo Burg CB Map	3 Mo Robb CB Map	3 Mo VT CB Map
6 Mo (9/1/2009 - 2/28/2010)	6 Mo Asslt CB Map	6 Mo Burg CB Map	6 Mo Robb CB Map	6 Mo VT CB Map
9 Mo (6/1/2009 - 2/28/2010)	9 Mo Asslt CB Map	9 Mo Burg CB Map	9 Mo Robb CB Map	9 Mo VT CB Map
12 Mo (3/1/2009 - 2/28/2010)	12 Mo Asslt CB Map	12 Mo Burg CB Map	12 Mo Robb CB Map	12 Mo VT CB Map
Measurement Crime Data (MCD)				
3 Mo MCD (3/1/2010 - 5/31/2010)	**3 Mo Assault MCD**	**3 Mo Burglary MCD**	**3 Mo Robbery MCD**	**3 Mo Vehicle Theft MCD**
	3 Mo Asslt CB Map n = 31 N = 1528 Hit rate % = .02 a = 8.99 A = 940.77 Area % = .01 PAI = 2	3 Mo Burg CB Map n = 124 N = 2857 Hit rate % = .04 a = 15.02 A = 940.77 Area % = .02 PAI = 2	3 Mo Robb CB Map n = 31 N = 810 Hit rate % = .04 a = 8.16 A = 940.77 Area % = .01 PAI = 4	3 Mo VT CB Map n = 20 N = 1001 Hit rate % = .02 a = 12.58 A = 940.77 Area % = .01 PAI = 2
	6 Mo Asslt CB Map n = 99 N = 1528 Hit rate % = .06 a = 14.99 A = 940.77 Area % = .02 PAI = 3	6 Mo Burg CB Map n = 270 N = 2857 Hit rate % = .09 a = 30.97 A = 940.77 Area % = .03 PAI = 3	6 Mo Robb CB Map n = 74 N = 810 Hit rate % = .09 a = 15.13 A = 940.77 Area % = .02 PAI = 4.5	6 Mo VT CB Map n = 45 N = 1001 Hit rate % = .04 a = 21.44 A = 940.77 Area % = .02 PAI = 2
	9 Mo Asslt CB Map n = 161 N = 1528 Hit rate % = .11 a = 19.35 A = 940.77 Area % = .02 PAI = 5.5	9 Mo Burg CB Map n = 350 N = 2857 Hit rate % = .12 a = 42.62 A = 940.77 Area % = .05 PAI = 2.4	9 Mo Robb CB Map n = 99 N = 810 Hit rate % = .12 a = 19.72 A = 940.77 Area % = .02 PAI = 6	9 Mo VT CB Map n = 71 N = 1001 Hit rate % = .07 a = 30.69 A = 940.77 Area % = .03 PAI = 2.33

	12 Mo Asslt CB Map n = 208 N = 1528 Hit rate % = .14 a = 27.14 A = 940.77 Area % = .03 PAI = 4.66	12 Mo Burg CB Map n = 422 N = 2857 Hit rate % = .15 a = 46.15 A = 940.77 Area % = .05 PAI = 3	12 Mo Robb CB Map n = 129 N = 810 Hit rate % = .16 a = 25.26 A = 940.77 Area % = .03 PAI = 5.33	12 Mo VT CB Map n = 90 N = 1001 Hit rate % = .09 a = 34.59 A = 940.77 Area % = .04 PAI = 2.25
6 Mo MCD (3/1/2010 - 8/31/2010)	**6 Mo Assault MCD**	**6 Mo Burglary MCD**	**6 Mo Robbery MCD**	**6 Mo Vehicle Theft MCD**
	3 Mo Asslt CB Map n = 72 N = 3155 Hit rate % = .02 a = 8.99 A = 940.77 Area % = .01 PAI = 2	3 Mo Burg CB Map n = 253 N = 6089 Hit rate % = .04 a = 15.02 A = 940.77 Area % = .02 PAI = 2	3 Mo Robb CB Map n = 68 N = 1663 Hit rate % = .04 a = 8.16 A = 940.77 Area % = .01 PAI = 4	3 Mo VT CB Map n = 62 N = 2200 Hit rate % = .03 a = 12.58 A = 940.77 Area % = .01 PAI = 3
	6 Mo Asslt CB Map n = 209 N = 3155 Hit rate % = .07 a = 14.99 A = 940.77 Area % = .02 PAI = 3.5	6 Mo Burg CB Map n = 541 N = 6089 Hit rate % = .09 a = 30.97 A = 940.77 Area % = .03 PAI = 3	6 Mo Robb CB Map n = 157 N = 1663 Hit rate % = .09 a = 15.13 A = 940.77 Area % = .02 PAI = 4.5	6 Mo VT CB Map n = 100 N = 2200 Hit rate % = .05 a = 21.44 A = 940.77 Area % = .02 PAI = 2.5
	9 Mo Asslt CB Map n = 326 N = 3155 Hit rate % = .10 a = 19.35 A = 940.77 Area % = .02 PAI = 5	9 Mo Burg CB Map n = 767 N = 6089 Hit rate % = .13 a = 42.62 A = 940.77 Area % = .05 PAI = 2.6	9 Mo Robb CB Map n = 217 N = 1663 Hit rate % = .13 a = 19.72 A = 940.77 Area % = .02 PAI = 6.5	9 Mo VT CB Map n = 164 N = 2200 Hit rate % = .07 a = 30.69 A = 940.77 Area % = .03 PAI = 2.33

	12 Mo Asslt CB Map n = 424 N = 3155 Hit rate % = .13 a = 27.14 A = 940.77 Area % = .03 PAI = 4.33	12 Mo Burg CB Map n = 902 N = 6089 Hit rate % = .15 a = 46.15 A = 940.77 Area % = .05 PAI = 3	12 Mo Robb CB Map n = 270 N = 1663 Hit rate % = .16 a = 25.26 A = 940.77 Area % = .03 PAI = 5.33	12 Mo VT CB Map n = 207 N = 2200 Hit rate % = .09 a = 34.59 A = 940.77 Area % = .04 PAI = 2.25
9 Mo MCD (3/1/2010 - 11/30/2010)	**9 Mo Assault MCD**	**9 Mo Burglary MCD**	**9 Mo Robbery MCD**	**9 Mo Vehicle Theft MCD**
	3 Mo Asslt CB Map n = 125 N = 4638 Hit rate % = .03 a = 8.99 A = 940.77 Area % = .01 PAI = 3	3 Mo Burg CB Map n = 390 N = 9597 Hit rate % = .04 a = 15.02 A = 940.77 Area % = .02 PAI = 2	3 Mo Robb CB Map n = 105 N = 2609 Hit rate % = .04 a = 8.16 A = 940.77 Area % = .01 PAI = 4	3 Mo VT CB Map n = 96 N = 3418 Hit rate % = .03 a = 12.58 A = 940.77 Area % = .01 PAI = 3
	6 Mo Asslt CB Map n = 311 N = 4638 Hit rate % = .07 a = 14.99 A = 940.77 Area % = .02 PAI = 3.5	6 Mo Burg CB Map n = 873 N = 9597 Hit rate % = .09 a = 30.97 A = 940.77 Area % = .03 PAI = 3	6 Mo Robb CB Map n = 243 N = 2609 Hit rate % = .09 a = 15.13 A = 940.77 Area % = .02 PAI = 4.5	6 Mo VT CB Map n = 167 N = 3418 Hit rate % = .05 a = 21.44 A = 940.77 Area % = .02 PAI = 2.5
	9 Mo Asslt CB Map n = 492 N = 4638 Hit rate % = .11 a = 19.35 A = 940.77 Area % = .02 PAI = 5.5	9 Mo Burg CB Map n = 1207 N = 9597 Hit rate % = .13 a = 42.62 A = 940.77 Area % = .05 PAI = 2.6	9 Mo Robb CB Map n = 329 N = 2609 Hit rate % = .13 a = 19.72 A = 940.77 Area % = .02 PAI = 6.5	9 Mo VT CB Map n = 263 N = 3418 Hit rate % = .08 a = 30.69 A = 940.77 Area % = .03 PAI = 2.67

	12 Mo Asslt CB Map n = 633 N = 4638 Hit rate % = .14 a = 27.14 A = 940.77 Area % = .03 PAI = 4.66	12 Mo Burg CB Map n = 1415 N = 9597 Hit rate % = .15 a = 46.15 A = 940.77 Area % = .05 PAI = 3	12 Mo Robb CB Map n = 416 N = 2609 Hit rate % = .16 a = 25.26 A = 940.77 Area % = .03 PAI = 5.33	12 Mo VT CB Map n = 318 N = 3418 Hit rate % = .09 a = 34.59 A = 940.77 Area % = .04 PAI = 2.25
12 Mo MCD (3/1/2010 - 2/28/2011)	**12 Mo Assault MCD**	**12 Mo Burglary MCD**	**12 Mo Robbery MCD**	**12 Mo Vehicle Theft MCD**
	3 Mo Asslt CB Map n = 159 N = 5699 Hit rate % = .03 a = 8.99 A = 940.77 Area % = .01 PAI = 3	3 Mo Burg CB Map n = 500 N = 12178 Hit rate % = .04 a = 15.02 A = 940.77 Area % = .02 PAI = 2	3 Mo Robb CB Map n = 141 N = 3349 Hit rate % = .04 a = 8.16 A = 940.77 Area % = .01 PAI = 4	3 Mo VT CB Map n = 134 N = 4533 Hit rate % = .03 a = 12.58 A = 940.77 Area % = .01 PAI = 3
	6 Mo Asslt CB Map n = 377 N = 5699 Hit rate % = .07 a = 14.99 A = 940.77 Area % = .02 PAI = 3.5	6 Mo Burg CB Map n = 1121 N = 12178 Hit rate % = .09 a = 30.97 A = 940.77 Area % = .03 PAI = 3	6 Mo Robb CB Map n = 304 N = 3349 Hit rate % = .09 a = 15.13 A = 940.77 Area % = .02 PAI = 4.5	6 Mo VT CB Map n = 221 N = 4533 Hit rate % = .05 a = 21.44 A = 940.77 Area % = .02 PAI = 2.5
	9 Mo Asslt CB Map n = 611 N = 5699 Hit rate % = .11 a = 19.35 A = 940.77 Area % = .02 PAI = 5.5	9 Mo Burg CB Map n = 1543 N = 12178 Hit rate % = .13 a = 42.62 A = 940.77 Area % = .05 PAI = 2.6	9 Mo Robb CB Map n = 428 N = 3349 Hit rate % = .13 a = 19.72 A = 940.77 Area % = .02 PAI = 6.5	9 Mo VT CB Map n = 331 N = 4533 Hit rate % = .07 a = 30.69 A = 940.77 Area % = .03 PAI = 2.33

	12 Mo Asslt CB Map n = 768 N = 5699 Hit rate % = .13 a = 27.14 A = 940.77 Area % = .03 PAI = 4.33	12 Mo Burg CB Map n = 1799 N = 12178 Hit rate % = .15 a = 46.15 A = 940.77 Area % = .05 PAI = 3	12 Mo Robb CB Map n = 549 N = 3349 Hit rate % = .16 a = 25.26 A = 940.77 Area % = .03 PAI = 5.33	12 Mo VT CB Map n = 404 N = 4533 Hit rate % = .09 a = 34.59 A = 940.77 Area % = .04 PAI = 2.25
Hotspot Mapping Technique: Grid				
	Assault	**Burglary**	**Robbery**	**Vehicle Theft**
Input Crime Data (ICD)				
3 Mo (12/1/2009 - 2/28/2010)	3 Mo Asslt Grid Map # of Points: 1088 Grid Cell Size: 233m	3 Mo Burg Grid Map # of Points: 2554 Grid Cell Size: 152m	3 Mo Robb Grid Map # of Points: 748 Grid Cell Size: 280m	3 Mo VT Grid Map # of Points: 1115 Grid Cell Size: 230m
6 Mo (9/1/2009 - 2/28/2010)	6 Mo Asslt Grid Map # of Points: 2437 Grid Cell Size: 155m	6 Mo Burg Grid Map # of Points: 6333 Grid Cell Size: 96m	6 Mo Robb Grid Map # of Points: 1763 Grid Cell Size: 183m	6 Mo VT Grid Map # of Points: 2266 Grid Cell Size: 161m
9 Mo (6/1/2009 - 2/28/2010)	9 Mo Asslt Grid Map # of Points: 3940 Grid Cell Size: 122 m	9 Mo Burg Grid Map # of Points: 9943 Grid Cell Size: 77m	9 Mo Robb Grid Map # of Points: 2884 Grid Cell Size: 143m	9 Mo VT Grid Map # of Points: 3425 Grid Cell Size: 131m
12 Mo (3/1/2009 - 2/28/2010)	12 Mo Asslt Grid Map # of Points: 5346 Grid Cell Size: 105 m	12 Mo Burg Grid Map # of Points: 12982 Grid Cell Size: 67m	12 Mo Robb Grid Map # of Points: 3799 Grid Cell Size: 124m	12 Mo VT Grid Map # of Points: 4476 Grid Cell Size: 115
Measurement Crime Data (MCD)				
3 Mo MCD (3/1/2010 - 5/31/2010)	**3 Mo Assault MCD**	**3 Mo Burglary MCD**	**3 Mo Robbery MCD**	**3 Mo Vehicle Theft MCD**
	3 Mo Asslt Grid Map n = 39 N = 1528 Hit rate % = .03 a = 1.19 A = 941 Area % = .001 PAI = 30	3 Mo Burg Grid Map n = 39 N = 2857 Hit rate % = .01 a = .83 A = 941 Area % = .001 PAI = 10	3 Mo Robb Grid Map n = 12 N = 810 Hit rate % = .01 a = .55 A = 941 Area % = .001 PAI = 10	3 Mo VT Grid Map n = 6 N = 1001 Hit rate % = .006 a = .58 A = 941 Area % = .001 PAI = 6

	6 Mo Asslt Grid Map n = 61 N = 1528 Hit rate % = .04 a = 1.25 A = 941 Area % = .001 PAI = 40	6 Mo Burg Grid Map n = 69 N = 2857 Hit rate % = .02 a = .83 A = 941 Area % = .001 PAI = 20	6 Mo Robb Grid Map n = 28 N = 810 Hit rate % = .03 a = 1.14 A = 941 Area % = .001 PAI = 30	6 Mo VT Grid Map n = 10 N = 1001 Hit rate % = .01 a = .83 A = 941 Area % = .001 PAI = 10
	9 Mo Asslt Grid Map n = 77 N = 1528 Hit rate % = .05 a = 1.55 A = 941 Area % = .002 PAI = 25	9 Mo Burg Grid Map n = 115 N = 2857 Hit rate % = .04 a = 1.16 A = 941 Area % = .001 PAI = 40	9 Mo Robb Grid Map n = 46 N = 810 Hit rate % = .06 a = .90 A = 941 Area % = .001 PAI = 60	9 Mo VT Grid Map n = 16 N = 1001 Hit rate % = .02 a = .72 A = 941 Area % = .001 PAI = 20
	12 Mo Asslt Grid Map n = 129 N = 1528 Hit rate % = .08 a = 1.97 A = 941 Area % = .002 PAI = 40	12 Mo Burg Grid Map n = 152 N = 2857 Hit rate % = .05 a = 1.45 A = 941 Area % = .002 PAI = 25	12 Mo Robb Grid Map n = 65 N = 810 Hit rate % = .08 a = 1.28 A = 941 Area % = .001 PAI = 80	12 Mo VT Grid Map n = 28 N = 1001 Hit rate % = .03 a = .85 A = 941 Area % = .001 PAI = 30
6 Mo MCD (3/1/2010 - 8/31/2010)	**6 Mo Assault MCD**	**6 Mo Burglary MCD**	**6 Mo Robbery MCD**	**6 Mo Vehicle Theft MCD**
	3 Mo Asslt Grid Map n = 82 N = 3155 Hit rate % = .03 a = 1.19 A = 941 Area % = .001 PAI = 30	3 Mo Burg Grid Map n = 90 N = 6089 Hit rate % = .01 a = .83 A = 941 Area % = .001 PAI = 10	3 Mo Robb Grid Map n = 24 N = 1663 Hit rate % = .01 a = .55 A = 941 Area % = .001 PAI = 10	3 Mo VT Grid Map n = 8 N = 2200 Hit rate % = .004 a = .58 A = 941 Area % = .001 PAI = 4

	6 Mo Asslt Grid Map n = 105 N = 3155 Hit rate % = .03 a = 1.25 A = 941 Area % = .001 PAI = 30	6 Mo Burg Grid Map n = 142 N = 6089 Hit rate % = .02 a = .83 A = 941 Area % = .001 PAI = 20	6 Mo Robb Grid Map n = 58 N = 1663 Hit rate % = .03 a = 1.14 A = 941 Area % = .001 PAI = 30	6 Mo VT Grid Map n = 27 N = 2200 Hit rate % = .01 a = .83 A = 941 Area % = .001 PAI = 10
	9 Mo Asslt Grid Map n = 154 N = 3155 Hit rate % = .05 a = 1.55 A = 941 Area % = .002 PAI = 25	9 Mo Burg Grid Map n = 252 N = 6089 Hit rate % = .04 a = 1.16 A = 941 Area % = .001 PAI = 40	9 Mo Robb Grid Map n = 85 N = 1663 Hit rate % = .05 a = .90 A = 941 Area % = .001 PAI = 50	9 Mo VT Grid Map n = 35 N = 2200 Hit rate % = .02 a = .72 A = 941 Area % = .001 PAI = 20
	12 Mo Asslt Grid Map n = 237 N = 3155 Hit rate % = .08 a = 1.97 A = 941 Area % = .002 PAI = 40	12 Mo Burg Grid Map n = 309 N = 6089 Hit rate % = .05 a = 1.45 A = 941 Area % = .002 PAI = 25	12 Mo Robb Grid Map n = 128 N =1663 Hit rate % = .08 a = 1.28 A = 941 Area % = .001 PAI = 80	12 Mo VT Grid Map n = 53 N = 2200 Hit rate % = .02 a = .85 A = 941 Area % = .001 PAI = 20
9 Mo MCD (3/1/2010 - 11/30/2010)	**9 Mo Assault MCD**	**9 Mo Burglary MCD**	**9 Mo Robbery MCD**	**9 Mo Vehicle Theft MCD**
	3 Mo Asslt Grid Map n = 126 N = 4638 Hit rate % = .03 a = 1.19 A = 941 Area % = .001 PAI = 30	3 Mo Burg Grid Map n = 137 N = 9597 Hit rate % = .01 a = .83 A = 941 Area % = .001 PAI = 10	3 Mo Robb Grid Map n = 31 N = 2609 Hit rate % = .01 a = .55 A = 941 Area % = .001 PAI = 10	3 Mo VT Grid Map n = 14 N = 3418 Hit rate % = .004 a = .58 A = 941 Area % = .001 PAI = 4

	6 Mo Asslt Grid Map n = 173 N = 4638 Hit rate % = .04 a = 1.25 A = 941 Area % = .001 PAI = 40	6 Mo Burg Grid Map n = 200 N = 9597 Hit rate % = .02 a = .83 A = 941 Area % = .001 PAI = 20	6 Mo Robb Grid Map n = 95 N = 2609 Hit rate % = .04 a = 1.14 A = 941 Area % = .001 PAI = 40	6 Mo VT Grid Map n = 40 N = 3418 Hit rate % = .01 a = .83 A = 941 Area % = .001 PAI = 10
	9 Mo Asslt Grid Map n = 229 N = 4638 Hit rate % = .05 a = 1.55 A = 941 Area % = .002 PAI = 25	9 Mo Burg Grid Map n = 346 N = 9597 Hit rate % = .04 a = 1.16 A = 941 Area % = .001 PAI = 40	9 Mo Robb Grid Map n = 141 N = 2609 Hit rate % = .05 a = .90 A = 941 Area % = .001 PAI = 50	9 Mo VT Grid Map n = 64 N = 3418 Hit rate % = .02 a = .72 A = 941 Area % = .001 PAI = 20
	12 Mo Asslt Grid Map n = 357 N = 4638 Hit rate % = .08 a = 1.97 A = 941 Area % = .002 PAI = 40	12 Mo Burg Grid Map n = 451 N = 9597 Hit rate % = .05 a = 1.45 A = 941 Area % = .002 PAI = 25	12 Mo Robb Grid Map n = 206 N = 2609 Hit rate % = .08 a = 1.28 A = 941 Area % = .001 PAI = 80	12 Mo VT Grid Map n = 85 N = 3418 Hit rate % = .02 a = .85 A = 941 Area % = .001 PAI = 20
12 Mo MCD (3/1/2010 - 2/28/2011)	**12 Mo Assault MCD**	**12 Mo Burglary MCD**	**12 Mo Robbery MCD**	**12 Mo Vehicle Theft MCD**
	3 Mo Asslt Grid Map n = 163 N = 5699 Hit rate % = .03 a = 1.19 A = 941 Area % = .001 PAI = 30	3 Mo Burg Grid Map n = 172 N = 12178 Hit rate % = .01 a = .83 A = 941 Area % = .001 PAI = 10	3 Mo Robb Grid Map n = 42 N = 3349 Hit rate % = .01 a = .55 A = 941 Area % = .001 PAI = 10	3 Mo VT Grid Map n = 19 N = 4533 Hit rate % = .004 a = .58 A = 941 Area % = .001 PAI = 4

	6 Mo Asslt Grid Map n = 232 N = 5699 Hit rate % = .04 a = 1.25 A = 941 Area % = .001 PAI = 40	6 Mo Burg Grid Map n = 259 N = 12178 Hit rate % = .02 a = .83 A = 941 Area % = .001 PAI = 20	6 Mo Robb Grid Map n = 122 N = 3349 Hit rate % = .04 a = 1.14 A = 941 Area % = .001 PAI = 40	6 Mo VT Grid Map n = 55 N = 4533 Hit rate % = .01 a = .83 A = 941 Area % = .001 PAI = 10
	9 Mo Asslt Grid Map n = 289 N = 5699 Hit rate % = .05 a = 1.55 A = 941 Area % = .002 PAI = 25	9 Mo Burg Grid Map n = 432 N = 12178 Hit rate % = .04 a = 1.16 A = 941 Area % = .001 PAI = 40	9 Mo Robb Grid Map n = 178 N = 3349 Hit rate % = .05 a = .90 A = 941 Area % = .001 PAI = 50	9 Mo VT Grid Map n = 80 N = 4533 Hit rate % = .02 a = .72 A = 941 Area % = .001 PAI = 20
	12 Mo Asslt Grid Map n = 454 N = 5699 Hit rate % = .08 a = 1.97 A = 941 Area % = .002 PAI = 40	12 Mo Burg Grid Map n = 567 N = 12178 Hit rate % = .05 a = 1.45 A = 941 Area % = .002 PAI = 25	12 Mo Robb Grid Map n = 268 N = 3349 Hit rate % = .08 a = 1.28 A = 941 Area % = .001 PAI = 80	12 Mo VT Grid Map n = 105 N = 4533 Hit rate % = .02 a = .85 A = 941 Area % = .001 PAI = 20
Hotspot Mapping Technique: Kernel Density (KD)				
	Assault	**Burglary**	**Robbery**	**Vehicle Theft**
Input Crime Data (ICD)				
3 Mo (12/1/2009 - 2/28/2010)	3 Mo Asslt KD Map	3 Mo Burg KD Map	3 Mo Robb KD Map	3 Mo VT KD Map
6 Mo (9/1/2009 - 2/28/2010)	6 Mo Asslt KD Map	6 Mo Burg KD Map	6 Mo Robb KD Map	6 Mo VT KD Map
9 Mo (6/1/2009 - 2/28/2010)	9 Mo Asslt KD Map	9 Mo Burg KD Map	9 Mo Robb KD Map	9 Mo VT KD Map
12 Mo (3/1/2009 - 2/28/2010)	12 Mo Asslt KD Map	12 Mo Burg KD Map	12 Mo Robb KD Map	12 Mo VT KD Map
Measurement Crime Data (MCD)				
3 Mo MCD (3/1/2010 - 5/31/2010)	**3 Mo Assault MCD**	**3 Mo Burglary MCD**	**3 Mo Robbery MCD**	**3 Mo Vehicle Theft MCD**

	3 Mo Asslt KD Map n = 888 N = 1528 Hit rate % = .58 a = 118.4 A = 941 Area % = .13 PAI = 4.46	3 Mo Burg KD Map n = 1836 N = 2857 Hit rate % = .64 a = 162.43 A = 941 Area % = .17 PAI = 3.76	3 Mo Robb KD Map n = 457 N = 810 Hit rate % = .56 a = 92.61 A = 941 Area % = .1 PAI = 5.6	3 Mo VT KD Map n = 524 N = 1001 Hit rate % = .52 a = 124.33 A = 941 Area % = .13 PAI = 4
	6 Mo Asslt KD Map n = 1077 N = 1528 Hit rate % = .7 a = 150.77 A = 941 Area % = .16 PAI = 4.38	6 Mo Burg KD Map n = 2023 N = 2857 Hit rate % = .71 a = 189.68 A = 941 Area % = .20 PAI = 3.55	6 Mo Robb KD Map n = 552 N = 810 Hit rate % = .68 a = 120.96 A = 941 Area % = .13 PAI = 5.23	6 Mo VT KD Map n = 619 N = 1001 Hit rate % = .62 a = 155.25 A = 941 Area % = .16 PAI = 3.88
	9 Mo Asslt KD Map n = 1144 N = 1528 Hit rate % = .75 a = 167.19 A = 941 Area % = .18 PAI = 4.17	9 Mo Burg KD Map n = 2043 N = 2857 Hit rate % = .72 a = 189.51 A = 941 Area % = .20 PAI = 3.6	9 Mo Robb KD Map n = 590 N = 810 Hit rate % = .73 a = 136.02 A = 941 Area % = .14 PAI = 5.21	9 Mo VT KD Map n = 667 N = 1001 Hit rate % = .67 a = 170.85 A = 941 Area % = .18 PAI = 3.72
	12 Mo Asslt KD Map n = 1167 N = 1528 Hit rate % = .76 a = 174.31 A = 941 Area % = .19 PAI = 4	12 Mo Burg KD Map n = 2047 N = 2857 Hit rate % = .72 a = 189.4 A = 941 Area % = .20 PAI = 3.6	12 Mo Robb KD Map n = 600 N = 810 Hit rate % = .74 a = 142.89 A = 941 Area % = .15 PAI = 4.93	12 Mo VT KD Map n = 692 N = 1001 Hit rate % = .69 a = 179.94 A = 941 Area % = .19 PAI = 3.63
6 Mo MCD (3/1/2010 - 8/31/2010)	**6 Mo Assault MCD**	**6 Mo Burglary MCD**	**6 Mo Robbery MCD**	**6 Mo Vehicle Theft MCD**

	3 Mo Asslt KD Map n = 1814 N = 3155 Hit rate % = .57 a = 118.4 A = 941 Area % = .13 PAI = 4.38	3 Mo Burg KD Map n = 3923 N = 6089 Hit rate % = .64 a = 162.43 A = 941 Area % = .17 PAI = 3.76	3 Mo Robb KD Map n = 913 N = 1663 Hit rate % = .55 a = 92.61 A = 941 Area % = .1 PAI = 5.5	3 Mo VT KD Map n = 1107 N = 2200 Hit rate % = .5 a = 124.33 A = 941 Area % = .13 PAI = 3.85
	6 Mo Asslt KD Map n = 2202 N = 3155 Hit rate % = .7 a = 150.77 A = 941 Area % = .16 PAI = 4.38	6 Mo Burg KD Map n = 4325 N = 6089 Hit rate % = .71 a = 189.68 A = 941 Area % = .20 PAI = 3.55	6 Mo Robb KD Map n = 1132 N = 1663 Hit rate % = .68 a = 120.96 A = 941 Area % = .13 PAI = 5.23	6 Mo VT KD Map n = 1329 N = 2200 Hit rate % = .6 a = 155.25 A = 941 Area % = .16 PAI = 3.75
	9 Mo Asslt KD Map n = 2344 N = 3155 Hit rate % = .74 a = 167.19 A = 941 Area % = .18 PAI = 4.11	9 Mo Burg KD Map n = 4381 N = 6089 Hit rate % = .72 a = 189.51 A = 941 Area % = .20 PAI = 3.6	9 Mo Robb KD Map n = 1215 N = 1663 Hit rate % = .73 a = 136.02 A = 941 Area % = .14 PAI = 5.21	9 Mo VT KD Map n = 1447 N = 2200 Hit rate % = .66 a = 170.85 A = 941 Area % = .18 PAI = 3.67
	12 Mo Asslt KD Map n = 2384 N = 3155 Hit rate % = .76 a = 174.31 A = 941 Area % = .19 PAI = 4	12 Mo Burg KD Map n = 4363 N = 6089 Hit rate % = .72 a = 189.4 A = 941 Area % = .20 PAI = 3.6	12 Mo Robb KD Map n = 1229 N = 1663 Hit rate % = .74 a = 142.89 A = 941 Area % = .15 PAI = 4.93	12 Mo VT KD Map n = 1497 N = 2200 Hit rate % = .68 a = 179.94 A = 941 Area % = .19 PAI = 3.58
9 Mo MCD (3/1/2010 - 11/30/2010)	**9 Mo Assault MCD**	**9 Mo Burglary MCD**	**9 Mo Robbery MCD**	**9 Mo Vehicle Theft MCD**

	3 Mo Asslt KD Map n = 2655 N = 4638 Hit rate % = .57 a = 118.4 A = 941 Area % = .13 PAI = 4.38	3 Mo Burg KD Map n = 6088 N = 9597 Hit rate % = .63 a = 162.43 A = 941 Area % = .17 PAI = 3.71	3 Mo Robb KD Map n = 1409 N = 2609 Hit rate % = .54 a = 92.61 A = 941 Area % = .1 PAI = 5.4	3 Mo VT KD Map n = 1704 N = 3418 Hit rate % = .50 a = 124.33 A = 941 Area % = .13 PAI = 3.85
	6 Mo Asslt KD Map n = 3186 N = 4638 Hit rate % = .69 a = 150.77 A = 941 Area % = .16 PAI = 4.31	6 Mo Burg KD Map n = 6741 N = 9597 Hit rate % = .70 a = 189.68 A = 941 Area % = .20 PAI = 3.5	6 Mo Robb KD Map n = 1757 N = 2609 Hit rate % = .67 a = 120.96 A = 941 Area % = .13 PAI = 5.15	6 Mo VT KD Map n = 2092 N = 3418 Hit rate % = .61 a = 155.25 A = 941 Area % = .16 PAI = 3.81
	9 Mo Asslt KD Map n = 3405 N = 4638 Hit rate % = .73 a = 167.19 A = 941 Area % = .18 PAI = 4.06	9 Mo Burg KD Map n = 6829 N = 9597 Hit rate % = .71 a = 189.51 A = 941 Area % = .20 PAI = 3.55	9 Mo Robb KD Map n = 1884 N = 2609 Hit rate % = .72 a = 136.02 A = 941 Area % = .14 PAI = 5.14	9 Mo VT KD Map n = 2267 N = 3418 Hit rate % = .66 a = 170.85 A = 941 Area % = .18 PAI = 3.67
	12 Mo Asslt KD Map n = 3461 N = 4638 Hit rate % = .75 a = 174.31 A = 941 Area % = .19 PAI = 3.95	12 Mo Burg KD Map n = 6807 N = 9597 Hit rate % = .71 a = 189.4 A = 941 Area % = .20 PAI = 3.55	12 Mo Robb KD Map n = 1923 N = 2609 Hit rate % = .74 a = 142.89 A = 941 Area % = .15 PAI = 4.93	12 Mo VT KD Map n = 2338 N = 3418 Hit rate % = .68 a = 179.94 A = 941 Area % = .19 PAI = 3.58
12 Mo MCD (3/1/2010 - 2/28/2011)	**12 Mo Assault MCD**	**12 Mo Burglary MCD**	**12 Mo Robbery MCD**	**12 Mo Vehicle Theft MCD**

	3 Mo Asslt KD Map n = 3282 N = 5699 Hit rate % = .58 a = 118.4 A = 941 Area % = .13 PAI = 4.46	3 Mo Burg KD Map n = 7691 N = 12178 Hit rate % = .63 a = 162.43 A = 941 Area % = .17 PAI = 3.71	3 Mo Robb KD Map n = 1793 N = 3349 Hit rate % = .54 a = 92.61 A = 941 Area % = .1 PAI = 5.4	3 Mo VT KD Map n = 2272 N = 4533 Hit rate % = .50 a = 124.33 A = 941 Area % = .13 PAI = 3.85
	6 Mo Asslt KD Map n = 3917 N = 5699 Hit rate % = .69 a = 150.77 A = 941 Area % = .16 PAI = 4.31	6 Mo Burg KD Map n = 8560 N = 12178 Hit rate % = .70 a = 189.68 A = 941 Area % = .20 PAI = 3.5	6 Mo Robb KD Map n = 2228 N = 3349 Hit rate % = .67 a = 120.96 A = 941 Area % = .13 PAI = 5.15	6 Mo VT KD Map n = 2792 N = 4533 Hit rate % = .62 a = 155.25 A = 941 Area % = .16 PAI = 3.88
	9 Mo Asslt KD Map n = 4179 N = 5699 Hit rate % = .73 a = 167.19 A = 941 Area % = .18 PAI = 4.06	9 Mo Burg KD Map n = 8667 N = 12178 Hit rate % = .71 a = 189.51 A = 941 Area % = .20 PAI = 3.55	9 Mo Robb KD Map n = 2390 N = 3349 Hit rate % = .71 a = 136.02 A = 941 Area % = .14 PAI = 5.07	9 Mo VT KD Map n = 3009 N = 4533 Hit rate % = .66 a = 170.85 A = 941 Area % = .18 PAI = 3.67
	12 Mo Asslt KD Map n = 4257 N = 5699 Hit rate % = .75 a = 174.31 A = 941 Area % = .19 PAI = 3.95	12 Mo Burg KD Map n = 8647 N = 12178 Hit rate % = .71 a = 189.4 A = 941 Area % = .20 PAI = 3.55	12 Mo Robb KD Map n = 2471 N = 3349 Hit rate % = .74 a = 142.89 A = 941 Area % = .15 PAI = 4.93	12 Mo VT KD Map n = 3115 N = 4533 Hit rate % = .69 a = 179.94 A = 941 Area % = .19 PAI = 3.63

Appendix C

Mean PAI Values for each Hotspot Mapping Technique

Hotspot Mapping Technique: Census Block (CB)

3 Mo Assault	3 Mo Burglary	3 Mo Robbery	3 Mo Vehicle Theft	PAI Totals	PAI Averages	PAI Average for Hotspot Mapping Technique
2	2	4	2	10		
3	3	4.5	2	12.5		
5.5	2.4	6	2.33	16.23		
4.66	3	5.33	2.25	15.24		
				53.97	53.97 / 16 = 3.37	
6 Mo Assault	6 Mo Burglary	6 Mo Robbery	6 Mo Vehicle Theft			
2	2	4	3	11		
3.5	3	4.5	2.5	13.5		
5	2.6	6.5	2.33	16.43		
4.33	3	5.33	2.25	14.91		
				55.84	55.84 / 16 = 3.49	
9 Mo Assault	9 Mo Burglary	9 Mo Robbery	9 Mo Vehicle Theft			
3	2	4	3	12		
3.5	3	4.5	2.5	13.5		14.07 / 4 = **3.52**
5.5	2.6	6.5	2.67	17.27		
4.66	3	5.33	2.25	15.24		
				58.01	58.01 / 16 = 3.63	
12 Mo Assault	12 Mo Burglary	12 Mo Robbery	12 Mo Vehicle Theft			
3	2	4	3	12		
3.5	3	4.5	2.5	13.5		

5.5	2.6	6.5	2.33	16.93		
4.33	3	5.33	2.25	14.91		
				57.34	57.34 / 16 = 3.58	

Hotspot Mapping Technique: Grid

3 Mo Assault MCD	3 Mo Burglary MCD	3 Mo Robbery MCD	3 Mo Vehicle Theft MCD	PAI Totals	PAI Averages	PAI Average for Hotspot Mapping Technique
30	10	10	6	56		
40	20	30	10	100		
25	40	60	20	145		
40	25	80	30	175		
				476	476 / 16 = 29.75	
6 Mo Assault MCD	6 Mo Burglary MCD	6 Mo Robbery MCD	6 Mo Vehicle Theft MCD			
30	10	10	4	54		
30	20	30	10	90		
25	40	50	20	135		
40	25	80	20	165		
				444	444 / 16 = 27.75	
9 Mo Assault MCD	9 Mo Burglary MCD	9 Mo Robbery MCD	9 Mo Vehicle Theft MCD			
30	10	10	4	54		
40	20	40	10	110		115.5 / 4 = **28.88**
25	40	50	20	135		
40	25	80	20	165		
				464	464 / 16 = 29	
12 Mo Assault MCD	12 Mo Burglary MCD	12 Mo Robbery MCD	12 Mo Vehicle Theft MCD			
30	10	10	4	54		
40	20	40	10	110		

25	40	50	20	135		
40	25	80	20	165		
				464	464 / 16 = 29	

Hotspot Mapping Technique: Kernel Density (KD)

3 Mo Assault MCD	3 Mo Burglary MCD	3 Mo Robbery MCD	3 Mo Vehicle Theft MCD	PAI Totals	PAI Averages	PAI Average for Hotspot Mapping Technique
4.46	3.76	5.6	4	17.82		
4.38	3.55	5.23	3.88	17.04		
4.17	3.6	5.21	3.72	16.7		
4	3.6	4.93	3.63	16.16		
				67.72	67.72 / 16 = 4.23	
6 Mo Assault MCD	6 Mo Burglary MCD	6 Mo Robbery MCD	6 Mo Vehicle Theft MCD			
4.38	3.76	5.5	3.85	17.49		
4.38	3.55	5.23	3.75	16.91		
4.11	3.6	5.21	3.67	16.59		
4	3.6	4.93	3.58	16.11		
				67.1	67.1 / 16 = 4.19	
9 Mo Assault MCD	9 Mo Burglary MCD	9 Mo Robbery MCD	9 Mo Vehicle Theft MCD			
4.38	3.71	5.4	3.85	17.34		
4.31	3.5	5.15	3.81	16.77		16.75 / 4 = **4.19**
4.06	3.55	5.14	3.67	16.42		
3.95	3.55	4.93	3.58	16.01		
				66.54	66.54 / 16 = 4.16	
12 Mo Assault MCD	12 Mo Burglary MCD	12 Mo Robbery MCD	12 Mo Vehicle Theft MCD			
4.46	3.71	5.4	3.85	17.42		
4.31	3.5	5.15	3.88	16.84		

4.06	3.55	5.07	3.67	16.35	
3.95	3.55	4.93	3.63	16.06	
				66.67	66.67 / 16 = 4.17

Appendix D

Mean PAI Values for each Crime Type

Hotspot Mapping Technique: Census Block (CB)				
Measurement Crime Data (MCD) over Input Crime Data (ICD)	**Assault**	**Burglary**	**Robbery**	**Vehicle Theft**
3 Mo MCD (3/1/2010 - 5/31/2010)				
3 Mo ICD Hotspot Map	2	2	4	2
6 Mo ICD Hotspot Map	3	3	4.5	2
9 Mo ICD Hotspot Map	5.5	2.4	6	2.33
12 Mo ICD Hotspot Map	4.66	3	5.33	2.25
6 Mo MCD (3/1/2010 - 8/31/2010)				
3 Mo ICD Hotspot Map	2	2	4	3
6 Mo ICD Hotspot Map	3.5	3	4.5	2.5
9 Mo ICD Hotspot Map	5	2.6	6.5	2.33
12 Mo ICD Hotspot Map	4.33	3	5.33	2.25
9 Mo MCD (3/1/2010 - 11/30/2010)				
3 Mo ICD Hotspot Map	3	2	4	3
6 Mo ICD Hotspot Map	3.5	3	4.5	2.5
9 Mo ICD Hotspot Map	5.5	2.6	6.5	2.67
12 Mo ICD Hotspot Map	4.66	3	5.33	2.25
12 Mo MCD (3/1/2010 - 2/28/2011)				
3 Mo ICD Hotspot Map	3	2	4	3
6 Mo ICD Hotspot Map	3.5	3	4.5	2.5
9 Mo ICD Hotspot Map	5.5	2.6	6.5	2.33
12 Mo ICD Hotspot Map	4.33	3	5.33	2.25

Hotspot Mapping Technique: Grid				
Measurement Crime Data (MCD) over Input Crime Data (ICD)	**Assault**	**Burglary**	**Robbery**	**Vehicle Theft**
3 Mo MCD (3/1/2010 - 5/31/2010)				
3 Mo ICD Hotspot Map	30	10	10	6
6 Mo ICD Hotspot Map	40	20	30	10
9 Mo ICD Hotspot Map	25	40	60	20
12 Mo ICD Hotspot Map	40	25	80	30
6 Mo MCD (3/1/2010 - 8/31/2010)				
3 Mo ICD Hotspot Map	30	10	10	4
6 Mo ICD Hotspot Map	30	20	30	10
9 Mo ICD Hotspot Map	25	40	50	20
12 Mo ICD Hotspot Map	40	25	80	20
9 Mo MCD (3/1/2010 - 11/30/2010)				
3 Mo ICD Hotspot Map	30	10	10	4
6 Mo ICD Hotspot Map	40	20	40	10
9 Mo ICD Hotspot Map	25	40	50	20
12 Mo ICD Hotspot Map	40	25	80	20
12 Mo MCD (3/1/2010 - 2/28/2011)				

3 Mo ICD Hotspot Map	30	10	10	4
6 Mo ICD Hotspot Map	40	20	40	10
9 Mo ICD Hotspot Map	25	40	50	20
12 Mo ICD Hotspot Map	40	25	80	20

Hotspot Mapping Technique: Kernel Density (KD)				
Measurement Crime Data (MCD) over Input Crime Data (ICD)	**Assault**	**Burglary**	**Robbery**	**Vehicle Theft**
3 Mo MCD (3/1/2010 - 5/31/2010)				
3 Mo ICD Hotspot Map	4.46	3.76	5.6	4
6 Mo ICD Hotspot Map	4.38	3.55	5.23	3.88
9 Mo ICD Hotspot Map	4.17	3.6	5.21	3.72
12 Mo ICD Hotspot Map	4	3.6	4.93	3.63
6 Mo MCD (3/1/2010 - 8/31/2010)				
3 Mo ICD Hotspot Map	4.38	3.76	5.5	3.85
6 Mo ICD Hotspot Map	4.38	3.55	5.23	3.75
9 Mo ICD Hotspot Map	4.11	3.6	5.21	3.67
12 Mo ICD Hotspot Map	4	3.6	4.93	3.58
9 Mo MCD (3/1/2010 - 11/30/2010)				
3 Mo ICD Hotspot Map	4.38	3.71	5.4	3.85
6 Mo ICD Hotspot Map	4.31	3.5	5.15	3.81
9 Mo ICD Hotspot Map	4.06	3.55	5.14	3.67
12 Mo ICD Hotspot Map	3.95	3.55	4.93	3.58
12 Mo MCD (3/1/2010 - 2/28/2011)				
3 Mo ICD Hotspot Map	4.46	3.71	5.4	3.85
6 Mo ICD Hotspot Map	4.31	3.5	5.15	3.88
9 Mo ICD Hotspot Map	4.06	3.55	5.07	3.67
12 Mo ICD Hotspot Map	3.95	3.55	4.93	3.63
PAI Totals	660.34	479.84	873.83	327.18
PAI Average for Hotspot Mapping Technique	660.34 / 48 = **13.76**	479.84 / 48 = **10**	873.83 / 48 = **18.2**	327.18 / 48 = **6.82**

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CURRICULUM VITAE

Zachary Thomas Vavra

Education

Indiana University-Purdue University Indianapolis May 2011-May 2015
Master of Science in Geographic Information Science

Boston University January 2006-March 2007
Financial Planning Online Certificate Program

Colorado Christian University August 2001-May 2005
Bachelor of Arts in Global Studies

Nizhni Novgorod State University January-April 2004
Russian Study Abroad Program

Work Experience

Study Abroad Advisor October 2007-present
Indiana University-Purdue University Indianapolis

- Advise a diverse student body on dozens of university sponsored study abroad programs
- Facilitate process of determining the transfer of credit for students studying abroad through an outside institution
- Coordinate with over 50 study abroad faculty directors on program promotion and application processing
- Monitor the processing of hundreds of study abroad applications per year
- Send around 400 students abroad per year
- Experience in managing international crises
- Coordinate and conduct over 50 classroom presentations per year promoting study abroad
- Administer pre-departure orientation sessions to prepare students traveling abroad
- Oversee the daily operations of the Study Abroad Office
  Organized and facilitated study abroad promotional events attended by hundreds of students per year

Assistant Language Teacher July 2005-July 2007
Yamagata, Japan Prefectural Board of Education

- Taught English to over 800 Japanese students at two high schools
- Responsible for preparing and administrating English lessons for 25 classes
- Created and administered international awareness classes.

Memberships

NAFSA: Association of International Educators October 2007-present

The Forum on Education Abroad October 2009-present

Conferences

CIEE Annual Conference November 2013
Minneapolis, Minnesota

Forum on Education Abroad Annual Conference April 2013
Chicago, Illinois

Forum on Education Abroad: The Code of Ethics September 2012
Indianapolis, Indiana

Forum on Education Abroad Annual Conference March 2012
Denver, Colorado

NAFSA Region VI Conference November 2011
Louisville, Kentucky

NAFSA Region VI Conference November 2010
Indianapolis, Indiana

NAFSA Indiana State Meeting June 2010
Bloomington, Indiana

- Presented on "Hot Topics in Education Abroad"

NAFSA Region VI Conference November 2009
Cincinnati, Ohio

NAFSA Region VI Conference November 2008
Lexington, Kentucky

- Presented on promoting study abroad using social media

NAFSA Annual Conference May 2008
Washington D.C.

NAFSA Region VI Conference November 2007
Indianapolis, Indiana

Community Involvement

International Homestay Host
Indianapolis, Indiana

- Hosted Swiss ESL student September 2010-February 2011
- Hosted Japanese university student August-December 2009

Coordinator November 2006 & November 2007
Asahi-machi, Japan

- Co-creator and organizer of largest cross-cultural event in Asahi-machi, over 200 attendees
- Delegated jobs and managed the work of 25 volunteers
- Tripled international monetary support from prior year

Workshop Instructor August 2006 & November 2006
Yamagata, Japan

- Yamagata Prefectural Mid-Year Seminar: Presented "Effective Internationalization"
- Yamagata Prefectural ALT Orientation Seminar: Presented “Making the Most of Your Yen”
- 45% of seminar attendees chose this workshop over 5 other workshops
- Workshop evaluated as “best and most helpful”

Adult Community English Teacher January-June 2006
Asahi-machi, Japan